Development of agricultural drought risk assessment model for Kermanshah Province (Iran), using satellite data and intelligent methods

Arshad S., Morid S., Reza Mobasheri M., Agha Alikhani M.

in

López-Francos A. (ed.).
Drought management: scientific and technological innovations

Zaragoza : CIHEAM
Options Méditerranéennes : Série A. Séminaires Méditerranéens; n. 80

2008
pages 303-310

Development of Agricultural Drought Risk Assessment Model for Kermanshah Province (Iran), using satellite data and intelligent methods

S. Arshad*, S. Morid*, M. Reza Mobasheri and M. Agha Alikhani***

*College of Agriculture, Tarbiat Modares University, P.O. Box 14115-336, Tehran, Iran

**College of Remote Sensing, Khaje Nasiredin Toosi University, P.O. Box 15875-4416, Tehran, Iran

SUMMARY – Agriculture sector has been affected by severe droughts during recent years in Iran. The existence of an agriculture drought warning system can be a useful means for preparedness and to reduce the consequent losses. This study develops a drought agricultural drought vulnerability assessment model using statistical and intelligent methods for Kermanshah province. The model is specific to rainfed wheat and barley and is able to assess real-time agricultural drought vulnerability associated with crop yield losses at critical phenological stages during the growing season. The model inputs are a combination of drought indices including: PDSI, Z-index, CMI, SPI and EDI, using genetic algorithm method. The model results show that the accurate rates are lower at the first stage than those during the later stages. Enhancement of the model with a Geographic Information System (GIS) has also made the model more capable for spatial analysis.

Key words: Vulnerability assessment, agricultural drought, Principle Component Analysis, Genetic Algorithm.

Introduction

Drought is a natural disaster that has a major economic impact on agriculture productions. It is very crucial to develop a warning system to detect potential agricultural drought risk at pre-planting and early crop-growth stages, using a number of indicators. Such a system enables decision makers to have sufficient time to implement strategies to reduce risk potential. The main indicator for drought monitoring are the indices. A drought index can be used to quantify: (i) the moisture condition of a region and thereby detect the onset and measure the severity of drought events, and (ii) the spatial extent of a drought event thereby allowing a comparison of moisture supply conditions between regions (Alley, 1984).

This issue has been objective of a number of studies. For instance Dietz *et al.* (1998) used growing-season climatic data (i.e. precipitation, temperature, evapotranspiration) to estimate drought risk. Wu and Wilhite (2004) developed an agricultural drought risk-assessment model on the basis of variables derived from the standardized precipitation index (SPI) and crop-specific drought index (CMI) using multivariate techniques. Quiring and Papakryiakou (2003) evaluated Palmer Drought Severity Index (PDSI), Z-index, SPI, and NOAA Drought Index (NDI) to measure agricultural drought.

This paper aims to develop an operational model to assess agricultural drought risk in Kermanshsh province. To illustrate the methodology, it is concentrated on the areas of rainfed wheat, which is the major crop in the study area.

Data and Methods

Study area and data

The Kermanshah Province as one of the main cereal-growing region is located in the western part of Iran, with total area of 24,980 km^2. Its annual precipitation varies from 375 to 500 mm. The total cropped are is about 820,000 hectares that rainfed area constitutes more than 75% of it. The province includes 11 provincial cities (PC) –administrative subdivisions, which are used later in the analysis (Fig. 1).

There are more than 100 meteorological stations in the Province, but due to the short period of records, only 20 stations are used here. The record length at these stations is from January 1971 to December 2004. There is also one meteorological agriculture research center (Sararud Station) that record phonological and physiological information of the crops, especially wheat. The yield data within the PCs were available for 39 years (1961-1999) that are recorded by the Kermanshah Agriculture Organization. The soil data (e.g. available water contact, AWC) were also prepared from the Forest and Pasture Organization.

The AVHRR images with 1.1 km resolution were used for this study. The sensor collects radiance data in five spectral bands, which are necessary to calculate the NDVI, VCI and TCI. The images were collected and preprocessed for an 18 years period of 1978 to 2006 (about 265 cloud free images).

Meteorological and satellite drought indices

Meteorological indices: The paper uses the time series of 5 drought indices – PDSI, SPI, EDI (Effective Drought Index), Z-index and CMI – which were shown to perform well for agricultural drought monitoring (Quiring and Papakryiakou, 2003).

To calculate amounts of the indices within the boundaries of the PCs and create their GIS layers, different spatial interpolation methods are applied and finally Weighted Moving Average (WMA) is selected. Most of these indices are calculated using climate data from the meteorological stations.

Satellite indices: The previous monitoring systems are faced with two main limitations that are lack of data in large areas and most importantly, difficulty in near-real time data collection. Application of the satellite-sensor data is a suitable solution to overcome the said limitation.

The Normalized difference vegetation index (NDVI) is the most well known satellite index derived from AVHRR that has been widely used to drought monitoring and evaluate vegetation coverage on Earth (Tucker and Choudhury, 1987). This index is based on vegetation behavior in reflecting solar electromagnetic spectrum in invisible (Ch1; 0.58 to 0.68 μm) and infra-red (Ch2; 0.725 to 1 μm) range and defined as follow:

$$NDVI = \frac{(Ch_2 - Ch_1)}{(Ch_2 + Ch_1)}$$

The NDVI is a base for a number of indices, too. The vegetation condition index (VCI) is one of them that is used here as an indicator for vegetation condition. The index is derived from the NDVI long-term mean. Temperature condition index (TCI) (Kogan, 1995) is also applied. The TCI reflects vegetation's response to temperature (the higher the temperature the more extreme the drought). TCI uses brightness temperature and represents the deviation of the current month's (week's) value from the recorded maximum (Thenkabail *et al.*, 2004). To incorporate the actual evapotranspiration, the crop-specific drought index (CSDI) (Meyer *et al.*, 1993) is applied:

The definition of CSDI is based on the ratio of actual evapotranspiration to potential evapotranspiration:

$$CSDI = \prod_{i=1}^{n} \left(\frac{\sum ET_{act}}{\sum ET_{pc}} \right)_i^{\lambda_i}$$

where ET_{act} and ET_{pc} are the actual and the potential evapotranspiration (mm) for the crop at each growth period; n the number of periods chosen to represent the crop's growth cycle; λ_i the relative sensitivity of the crop to moisture stress during the i^{th} period of growth. To estimate ET_{act}, the Surface Energy Balance Algorithm for Land (SEBAL) algorithm (Bastiaanssen *et al.*, 1998), which is developed based on satellite-sensor data, is applied. We also developed a new indices that is standardized CDSI (S-CSDI) that shows promising results as follow.

$$CSDI = \frac{(CSD\grave{I} - CSD\acute{I}_{\min})}{(CSDI_{\max} - CSDI_{\min})} \times 100$$

More about the indices and its performance is avaible in Arshad (2008).

Critical phenological stages and yield departure

Critical phenological stages: These stages are defined to enable the model to be updated during the growing season. For this, five periods are defined for wheat, including: vegetative, blooming, pod formation, pod fill, and ripening (Table 1). Using the simultaneous weather and phenology data from the Sararud stations, the dates of these periods are calculated based on the growing degree days (GDD). Furthermore, the GDD maps are created for the PCs, using the meteorological stations and GIS.

Table 1. The dates for phenological stages

Stage	Period	Date
First	Germination	10th week
Secound	Vegetative growth	19th week
Third	Initiation of flowering	20th week
Fourth	Grain filling	22th week
Fifth	Maturity	25th week

Yield Departure: As it is expected, there is a positive trend in the 39 years yield data, due to farming innovations. The data are de-trended by regressing the average annual yield against the year-of-harvest for each PC (Babb *et al*., 1997). The resulting un-standardized residuals (hereafter referred to as yield departures) are calculated for each PC and used in development and evaluation of the yield models. To use a standard criterion to indicate risk, 5 stages are defined based on standard deviation (s) of the yield departures (Zhang, 2004) and it is shown in Table 2.

Table 2. The categories of agricultural losses

Yield Category	Yield Residual
Extremely Loss	$> 1.17\ \sigma$
Moderately Loss	$1.17\ \sigma > Y > 0.33\ \sigma$
Normal	$0.33\ \sigma > Y > 0.33\ \sigma$
Moderately Increase	$-0.33\ \sigma > Y > -1.17\ \sigma$
Extremely Increase	$< -1.17\ \sigma$

Results and Discussion

Characteristics of the Drought Risk Assessment Model

The following characteristics have been considered for the proposed model. First, the risk assessment will be specifically based on rainfed wheat as the region's major crop to exhibit different sensitivities to water stress. Second, this study will integrate a few well-developed meteorological and satellite data indices as moisture supply indicators. Third, the intelligent techniques will be applied to selection of the best suitable indices. Fourth, the risk will be assessed at critical crop times during the growing season, and the moisture indicators will be updated as the crop develops. And, finally, the model will be enhanced with geographical information system (GIS).

The Model inputs

The meteorological based inputs: The weekly, monthly and three month values the PDSI, Z-index, EDI, CDSI and CMI are used as independent variables, indicating moisture supplies before and during the crop growing season. These indices are calculated for the selected stations and then their respected GIS layers are prepared. More than 14,000 layers are created and then average values of the indices, extracted for each PC. To lessen the number of variables and reducing the statistical interdependence, the principal components analysis (PCA) is also performed (Meyer *et al.*, 1993). The first three PCs are able to explain 90% of the total variance of the indices. Table 3 shows the list of independent variables for the model.

The satellite based Inputs: As it is already pointed out, the VCI, TCI and CWSI are satellite indices that are used as indicators for vegetation condition, soil water supply and actual evapotranspiration. Huge calculations are performed for preprocessing and processing of the images to calculate the indices that are not explained here due to space limitation. As an example, Fig. 1 shows status of the region based on these indices in 6- Mar-2004.

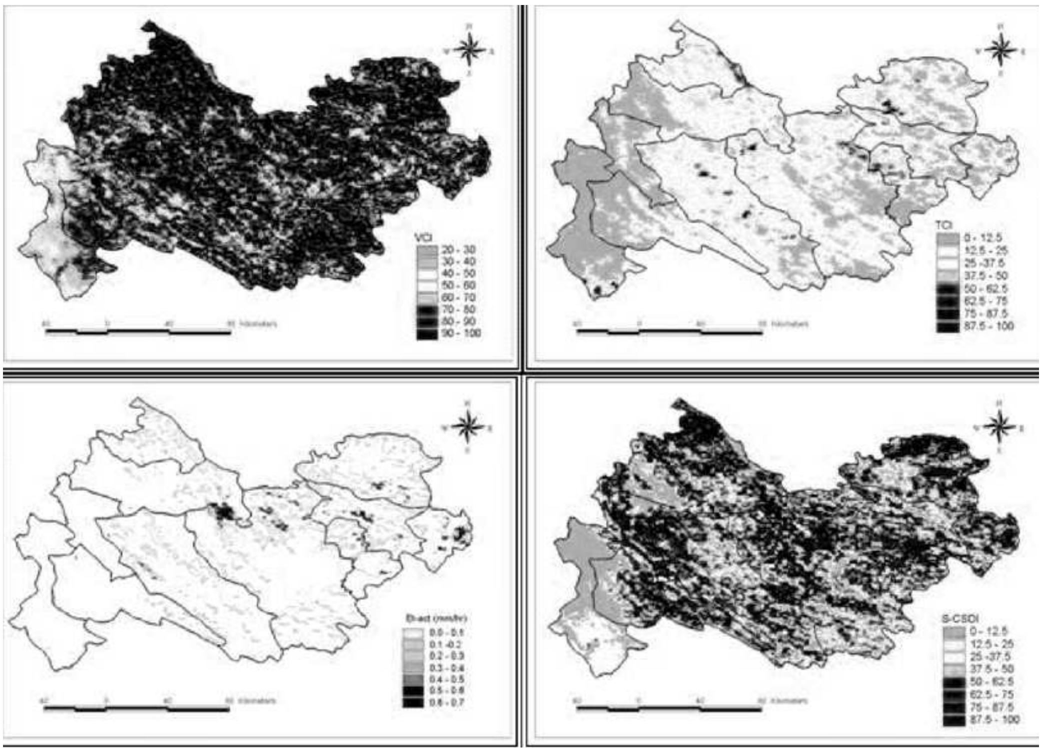

Fig. 1. Images of VCI, TCI, ETa and CSDI in Kermanshah province at 6- Mar-2004.

Selection of the inputs, using GA-ANN Algorithm Approach

Due to having a large number of inputs (refer to Table 1), it is necessary to evaluate and select them for the models (the models relating to 5 crop growing stages). This is fulfilled in two steps. In the first step, the best combination of the variables is screened using Genetic Algorithm (GA) technique and artificial neural network (ANN). Within a two-way process, the GA creates a population from the variables and its performance is checked by the ANN. In an iterative calculation, the best population (the ones that caused best performance of ANN) is evolved. This calculation repeated for all of the 5 stages and the results are shown in Table 3. The sign (√) refers to initial variables and (+√) refers to GA-ANN selection. It is worthy to mention that the number of pattern is not enough suitable to develop the final risk-assessment model by the ANN.

Table 3. Feature variables used in the discriminant analysis at each critical phenological stage for wheat

Variables (STB)	St. 1	St. 2	St. 3	St. 4	St. 5	Variables (STB)	St. 1	St. 2	St. 3	St. 4	St. 5	Variables (SB)	St. 1	St. 2	St. 3	St. 4	St. 5
3rd month's SPI	√+					23rd week's Z-index					√++	VCI-stage 1	√				
3rd month's PDSI	√					24th week's CMI					√	VCI-stage 2		√			
3rd month's Z-index	√					24th week's Z-index					√ +	VCI-stage 3			√		
3rd month's SPI-3	√ ++	√ ++	√ ++			25th week's CMI					√+	VCI-stage 4				√	
3rd month's PDSI-3	√					25th week's Z-index					√	VCI-stage 5					√
3rd month's Z-index-3	√ ++	√ ++				5th month's SPI					√	TCI-stage 1	√				
19th week's CMI		√				5th month's Z-index					√	TCI-stage 2		√			
19th week's PDSI		√				First PC of 3rd month	√+					TCI-stage 3			√		
19th week's Z-indexl		√				Second PC of 3rd month	√++					TCI-stage 4				√	
19th week's EDI		√ +	√ ++			Third PC of 3rd month	√					TCI-stage 5					√
5th month's SPI		√ +				First PC of 19th week		√				CSDI-stage 1	√				
5th month's PDSI			√			Second PC of 19th week		√				CSDI-stage 2		√			
5th month's Z-index		√ ++	√ ++			Third PC of 19th week		√				CSDI-stage 3			√		
20th week's CMI			√ +	√ ++	√ ++	First PC of 5th month		√	√			CSDI-stage 4				√	
20th week's PDSI			√			Second PC of 5th month			√ +		√ ++	CSDI-stage 5					√
20th week's Z-index			√			Third PC of 5th month		√	√ +			S-CSDI-stage 1	√				
20th week's EDI			√			First PC of 20th week			√			S-CSDI-stage 2		√			
22nd week's CMI				√	√	Second PC of 20th week			√ +			S-CSDI-stage 3			√		
22nd week's PDSI				√	√ +	Third PC of 20th week			√			S-CSDI-stage 4				√	
22nd week's Z-index				√ +	√	First PC of 22nd week				√		S-CSDI-stage 5					√
22nd week's EDI				√ +	√	Second PC of 22nd week			√ +								
23rd week's CMI					√ ++	Third PC of 22nd week				√							

St. = Stage

Intital Varibales √
Step 1: Selected variables by GA-ANN √ +
Step 2: Slected variables by Stepwise Reg. √ ++

Development of the Risk Assessment Model

Multiple regression technique is used to develop the final Assessment Model, using the selected variables from the previous calculations. This is applied independently for each of the growing stages to predict wheat production of the PCs. To increase degree of freedom of the regression model, once again the screening performed to reduce number of variables. But, this time the useful variables are selected by stepwise elimination of non-significant variables. The coefficient of determination R^2 is used to measure goodness-of-fit of the model, or closeness of the relationship between the indices and the relative yield departure in each PC. In all the statistical tests in the study, we used P=0.01 as the cutoff for rejection of the null hypothesis.

Evaluation of the Risk-Assessment Model

The performances of the models are evaluated using by R^2, *RMSE* (residual mean square error) and *d* (agreement index) (Quiring and Papakryiakou, 2003) that are commonly used for such validation. The best performance of the model yields R^2 and *d* equal to 1 and in case of *RMSE*, it is zero.

Another approach that is applied for evaluation, uses the classification of Table 2 and a special ranking. In that, rank 1 means that estimated class of damage/increase is same as the observed one. In rank 2, the model has correctly predicted the damage, but the intensity is different. Rank 3 express the situation that the model has predicted damage or increase in production, while the normal condition has been observed. Finally, in rank 4, the model has predicted damage or increase in production, while it is vise versa in reality. The results for these evaluations are shown in Fig. 2. Figure 2(b) illustrates better performance of the satellite indices based model. Figure 3 also shows linkage of the models and GIS and their predictions in the 1999 drought.

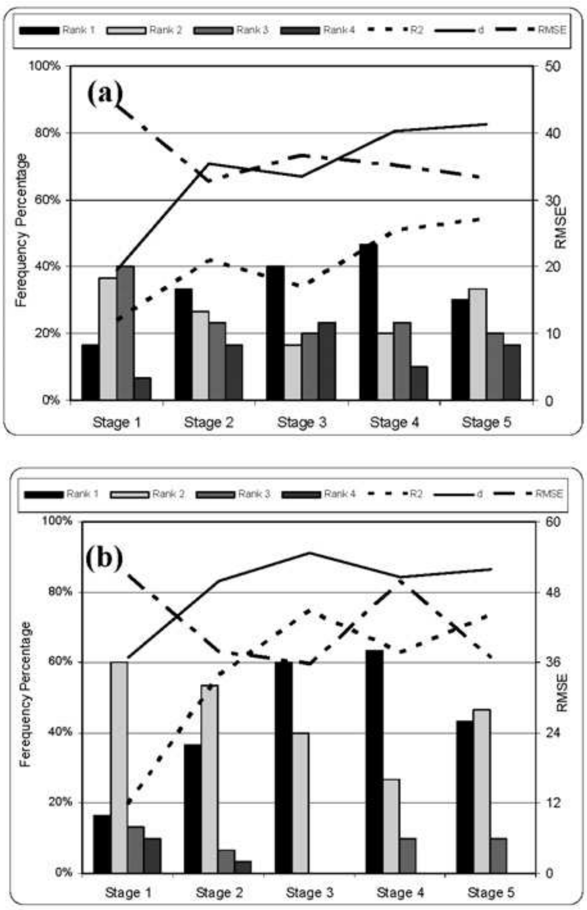

Fig. 2. Result of the evaluation of the models: a) meteorological indices based model; b) satellite indices based model.

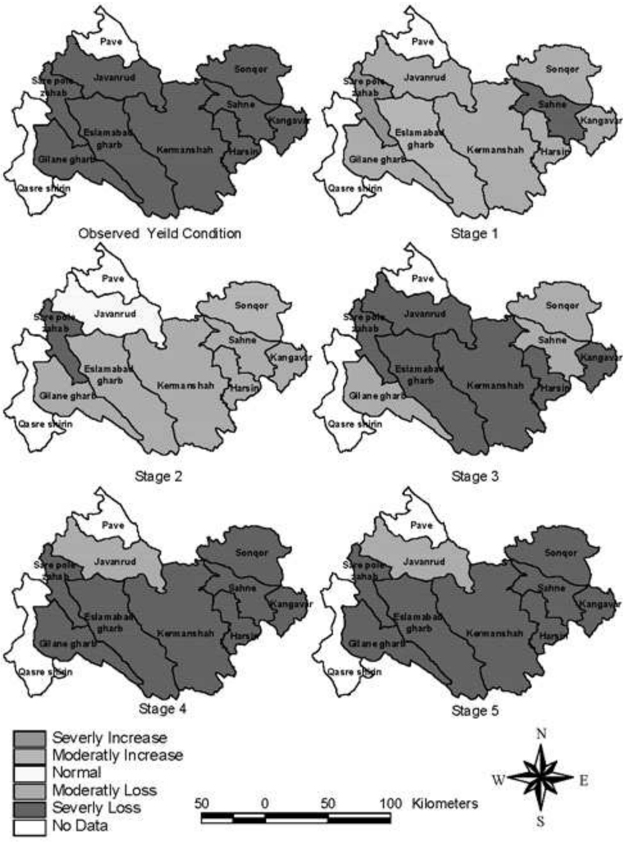

Fig. 3. Agricultural drought risk assessment through the 5 stages for non-irrigated wheat in 1999.

Conclusion

This research work is aimed to develop a near real time model to assess agricultural drought risk on the Kermashah rainfed areas (wheat) at 5 critical times by retaining previous, and adding current, weather information and satellite information as the crop passes through its various growth stages. The following conclusions can be drawn from this study:

(i) Among the meteorological indices, CMI, EDI, SPI and PDSI had the best performance, respectively to describe features of moisture supply before and during the growing season that affect a crop's final yield.

(ii) In general, the performance of the risk assessment model at the beginning stage is not reliable, but the accuracy improves with the growth stages as the crop develops. In early May, when wheat reaches at blooming stage, assessment accuracy improves significantly. The average correct assessment possibility gets to 50%, using meteorological indices and 71%, using satellite base indices, indicating that a reliable assessment for wheat begins at this point.

(iii) The satellite indices based model performed better. Also, among the applied satellite indices, S-CDSI that is suggested through this research work, improved significantly the results.

(iv) The GA-ANN algorithm, is an effective approach to select the suitable input variable for the risk assessment model.

References

Alley, W.M. (1984). The Palmer Drought Severity Index: Limitation and assumptions. *J. Climate Appl. Meteor.,* Vol. 23: 1100-1109.

Arshad, S. (2008). *Development of Agricultural Drought Risk Assessment Model, using Satellite data.* PhD dissertation, Tarbit Modares University, Iran.

Babb, J.C., Khandekar, M.L. and Garnett, E.R. (1997). An analysis of PNA indices for forecasting summer weather over Canadian prairies with implications for wheat yield and protein. In: *Proceedings of the Longe-Range Weather and Crop Forecasting Work Group Meeting III.* Canadian Meteorological Center, Dorval, QB, pp. 31-36.

Bastiaanssen, W.G.M., Menenti, M., Feddes, R.A. and Holtslag, A.A.M. (1998). A remote sensing surfsce energy balance algorithm for land (SEBAL), 1. Formulation. *Journal of Hydrology,* 212-213: 198-212.

Dietz, T.J., Put, M. and Subbiah, S. (1998). Drought risk assessment for dryland agriculture in semi-arid Telangana, Andhra Pradesh, India. In: H.J. Bruins (ed.), *The Arid Frontier: Interactive Management of Environment and Development*, Chap. 8. Kluwer Academic Publishers, Dordrecht, Netherlands, pp. 143-161.

Kogan, F.N. (1995). Droughts of the late 1980s in the United States as derived from NOAA polar-orbiting satellite data. *Bulletin of the American Meteorological Society*, 76: 655-668.

Meyer, S.J., Hubbard K.G. and Wilhite, D.A. (1993). A crop-specific drought index for corn: I. model development and validation. *Agronomy Journal*, Vol. 86: 388-395.

Quiring, S.M. and Papakryiakou, T.N. (2003). An evaluation of agricultural drought indices for the Canadian prairies. *Journal of Agricultural and forest Meteorology*, 1: 46-62.

Svoboda, M., LeComte, D., Hayes, M., Heim, R., Gleason, K., Angel, J. and Stephens, S. (2002). The drought monitor. *The Bulletin of the American Meteorological Society*, No. 83: 1181-1190.

Thenkabail, P.S., Gamage, M.S.D.N., Smakhtin, V.U. (2004). *The use of remote sensing data for drought assessment and monitoring in Southwest Asia*. Research Report 85. Colombo, Sri Lanka: International Water Management Institute.

Tian, G., Jupp, D.L.B., Yi, Q., McVicar, T.R. and Li, F. (1997). *Monitoring soil moisture effects and droughy using AVHRR satellite data. II: Application.* Technical report. CSIRO Earth Observation Center, Canberra, Australia.

Wu, H. and Wilhite, D.A. (2004). An operational agricultural drought risk assessment model for Nebraska, USA. *Natural Hazards*, Vol. 33: 1-21.

Zhang, J. (2004). Risk assessment of drought disaster in the maize-growing region of Songliao Plain, China. *Agriculture, Ecosystems and Environment*, Vol.102: 133-153.